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Abstract

Since Galí [1999], long-run restricted VARs have become the standard for identifying the effects of technology shocks. In a recent paper, Francis et al. [2008] proposed an alternative to identify technology as the shock that maximizes the forecast-error variance share of labor productivity at long horizons. In this paper, we propose a variant of the Max Share identification, which focuses on maximizing the variance share of labor productivity in the frequency domain. We consider the responses to technology shocks identified from various frequency bands. Two distinct technology shocks emerge. An expansionary shock increases productivity, output, and hours at business-cycle frequencies. The technology shock that maximizes productivity in the medium and long runs instead has clear contractionary effects on hours, while increasing output and productivity.

JEL: C32, C50, E32.

Keywords: Aggregate fluctuations; Business cycle; Frequency domain; Technology shocks; Vector autoregressions.

1 Introduction

Estimated impulse responses identified from VARs are often used to distinguish between competing macroeconomic theories. For example, using long-run restrictions, Galí [1999] and Francis and Ramey [2005] found that hours decline in response to a positive technology shock and argued that this provided evidence invalidating the standard RBC model in favor of sticky price models. This conclusion, however, appears to depend on the specification of hours in the VAR.[1] The salient result is that if specified in differences, hours contract. On the other hand, Christiano et al. [2003] found that if specified in levels, hours respond positively on impact. Arguing that hours per capita should be stationary fails to provide any resolution: Pesavento and Rossi [2005] showed that when the hours process is presumed stationary but close to a unit root, hours contract.

More recently, a few papers have attempted to resolve these conflicting results by examining the manner in which productivity and hours are detrended. Fernald [2007] proposed that productivity growth and hours had simultaneous shifts in mean. He argued that the shifts in productivity growth did not reflect technological innovation and should, therefore, be removed. One solution was to demean the series, while allowing for multiple breaks in the intercept, which confirmed the finding of a contraction in hours.[2] Francis and Ramey [2009] argued that the apparent unit root in hours was caused by changing demographic trends; once properly detrended, hours declined on impact.[3] Gospodinov et al. [2009], on the other hand, argued that if one is interested in preserving the underlying comovements between productivity and hours, the VAR should be estimated with hours in levels and not detrended. In this case, they found that hours rise following a technology shock. Thus,

[1] Others have used sign restrictions to identify technology shocks. Dedola and Neri [2007] employed restrictions recovered from a DSGE model. Peersman and Straub [2007] used restrictions recovered from a New Keynesian model. Both found neutral technology shocks to be expansionary on impact.

[2] This is similar to the recommendation of Canova et al. [2010], who argue against detrending the hours series.

[3] Galí and Rabanal [2005] also showed that neutral technology shocks are contractionary when hours is detrended.

how the VAR distinguishes between models appears to depend on whether one believes the low-frequency comovements can be attributed to technology.

Although long-run restrictions have been the popular choice for identification, macro models also have implications for the effect of technology shocks at non-zero frequencies. For example, the RBC literature [see Prescott, 1986] typically assumes that the business-cyle frequencies of the data (hours, output, investment, consumption) are driven solely by technology shocks.[4] Thus, an alternative to identifying technology shocks using long-run restrictions is to impose restrictions on the effect of technology shocks at non-zero frequencies. In particular, we identify the shock that maximizes the share of the forecast-error variance (FEV) in productivity growth and hours at various frequencies in a standard bivariate VAR. We consider business-cycle frequencies identified using linear filters: the HP_{1600} filter and the band-pass (BP) filter for periods between 8 and 32 quarters. We also consider medium-term cycles identified by the BP filter for periods of either 32-80 or 80-200 quarters. Our identification is adapted to the frequency domain from the method introduced by Faust [1998] and extended to technology shocks in Francis et al. [2008] (FOR).[5] We analyze the effect of varying the frequency window on the identified the shocks. As in Fernald [2007], we account for the low-frequency comovement between productivity growth and hours by demeaning the two series and allowing for two breaks in mean.

Two distinct technology shocks emerge. When identified from frequencies lower than the business cycle, technology shocks have Schumpeterian effects [Caballero and Hammour, 1994, 1996, Canova et al., 2007]. While productivity increases persistently, output responds ambiguously on impact, with both positive and negative draws, and increases eventually. These shocks have a clear contractionary effect on hours, which fall on impact and converge to

[4] Hansen [1997] pointed out that RBC models driven by persistent, but stationary, technology shocks and models driven by I(1) shocks have similar implications at business-cycle frequencies.

[5] The identification in FOR is similar in flavor to Uhlig's [2004] medium-run identification. Uhlig argued that other shocks (e.g., dividend tax shocks) could have long-run effects on productivity and, thus, confound the Galí [1999] identification. Like FOR, Uhlig computed the FEV share but, instead, calibrated it to a value determined by Monte Carlo simulations from a theoretical model.

zero from below. Interestingly, the shocks that drive productivity in the medium term (32-80 and 80-200 quarters) are indistinguishable from each other and from the shock identified with long-run restrictions. On the other hand, when identified from business-cycle frequencies, technology shocks are expansionary, inducing positive comovement of ouptut, hours, and productivity, and are broadly consistent with the predictions of an RBC model. The shocks identified by the HP_{1600} and the $BP_{8,32}$ filters are almost identical.

The balance of the paper is organized as follows: Section 2 describes the baseline structural VAR and the identification problem. In this section, we also discuss the issues of inference using long-run restrictions in small samples. Section 3 presents our alternative frequency-based identification. Section 4 compares the results across different frequency windows used for identification. Section 5 summarizes and offers some conclusions.

2 The Baseline Structural VAR

Consider the reduced-form VAR(p) representation of the $(n \times 1)$ vector of variables Y_t:

$$Y_t = A\left(L\right) Y_{t-1} + u_t, \tag{1}$$

where $A\left(L\right)$ is a matrix polynomial in the lag operator, L, of order p. The reduced-form residuals, u_t, have zero mean, i.e., $E\left(u_t\right) = 0$, and covariance matrix Σ, i.e., $E\left(u_t u_t'\right) = \Sigma$. We can rewrite (1) as

$$Y_t = A\left(L\right) Y_{t-1} + C\varepsilon_t,$$

where $C \equiv \left(A_0\right)^{-1}$. The structural matrix, A_0, maps the reduced-form residuals into the structural shocks, ε_t, where $E\left(\varepsilon_t \varepsilon_t'\right) = I$.

The central issue in the structural VAR literature involves the identification of the structural matrix, A_0. It is well known that infinitely many possible structural matrices can be derived from the decomposition of the reduced-form variance-covariance matrix, Σ. Various methods have been used to impose sufficient identifying restrictions. Short-run identifications, for example, impose restrictions directly on the elements of the structural matrix. While short-run identification schemes have proven less controversial econometrically, they typically are imposed through (potentially ad hoc) recursive ordering restrictions and may, therefore, be less economically appealing.

Long-run restrictions, on the other hand, are often more consistent with theoretical models. For example, technology shocks are often thought of as important drivers of business cycles in RBC models. Thus, the empirical literature has used VARs to identify technology shocks assuming that they are the sole source of the unit root in labor productivity [see, e.g., Galí, 1999]. This identifying assumption is implemented in VARs by imposing that non-technology shocks have no long-run—i.e., the frequency-zero—effect on labor productivity. Long-run restrictions identify the structural matrix, A_0, using restrictions of the form

$$\left\{\left[I - A\left(1\right)\right]^{-1} C\right\}_{ij} = 0, \tag{2}$$

which impose that shock j has no long-run effect on variable i.

Long-run restrictions—despite their theoretical appeal—have been shown to have some drawbacks. Based on arguments initially made by Sims [1972] and Faust and Leeper [1997], Christiano et al. [2006] contended that, in general, biases in the impulse responses of a VAR depend on two components: propagation (i.e., misspecifying the companion matrix for the VAR) and identification of the structural matrix (i.e., incorrectly choosing C). The former should be invariant to the identification strategy. Christiano et al. [2006] advocated for short-run restrictions on the basis that identification of C relies on the estimate of Σ only. Identification of C via long-run restrictions, on the other hand, relies on the estimate of Σ and the estimates of the As via the use of $A\left(1\right)$ in (2). Because the VAR is truncated, the estimate of $A\left(1\right)$ may have greater bias when the actual share of the spectral density of the data is not large near frequency zero. That is, we may encounter inference problems when we use the spectral density at the zero frequency as an input to the identification if there is not much information at the zero frequency.

In many models, there is a long-run interpretation of the shocks, and the spectral density near frequency zero may be sufficiently high to accurately estimate $A(1)$. But what happens when it is not? The solution proposed by Christiano et al. [2006] is an alternative estimator, based on the Bartlett estimator which is aimed at estimating $A(1)$ more accurately. Another alternative advocated by FOR is to examine theoretically-consistent identifying restrictions that do not depend so heavily on the zero frequency.

3 Identifying Shocks in the Frequency Domain

We describe how to identify the structural shock that maximizes (or minimizes) the share of the FEV of a given variable in the frequency domain.[6] The method can be applied to any frequency window, including the entire spectrum. Define the matrix D as the Cholesky factor of Σ and ς_i as the ith colum vector of D. We will refer to the set of ς_i as the Cholesky shocks. Then, all of the possible impulse vectors, $\xi(\alpha)$, resulting from exact identification can be expressed as a linear combination of the Cholesky shocks as follows: $\xi(\alpha) = \alpha' D$, where $(\alpha'\alpha) = 1$. Put differently, α is a column of a rotation matrix that maps the Cholesky shocks into another set of structural shocks. The goal of the procedure that follows is to generate α.

In particular, we consider the component of the FEV of the variable of interest identified by a linear filter, $\Gamma(\omega)$. For convenience, we can first map the variables in Y_t into other variables of interest in the vectors $\tilde{Y}_t$ and $\bar{Y}_t$ as follows:

$$\bar{Y}_t = F(L)^{-1} Y_t, \tag{3}$$

$$\tilde{Y}_t = G(L)\bar{Y}_t = G(L) F(L)^{-1} Y_t, \tag{4}$$

where $F(L)$ and $G(L)$ are matrix polynomials in the lag operator. The matrix $F(L)$ may be used, for example, to convert some of the elements of Y_t into differences, while $G(L)$ redefines some variables (e.g., transforming output and hours into labor productivity).

[6] The construction of the FEV shares in the frequency domain follows Altig et al. [2005].

The spectral density of $\tilde{Y}_t$ is given by:

$$S_{\tilde{Y}}\left(e^{-i\omega}\right) = H\left(e^{-i\omega}\right)\Sigma H\left(e^{-i\omega}\right)', \tag{5}$$

where $H\left(e^{-i\omega}\right) \equiv \left\{G\left(e^{-i\omega}\right)F\left(e^{-i\omega}\right)^{-1}\left[I - A\left(e^{-i\omega}\right)\right]^{-1}\right\}$. Given a structural shock (i.e., a vector α) and a linear filter with gain $\Gamma(\omega)$, the share of the FEV of variable j due to α is given by[7]:

$$V_{\tilde{Y}_j}(\alpha) = \alpha' \frac{\left[\int_{-\pi}^{\pi}\Gamma(\omega)\, S_{\tilde{Y}_j}\left(e^{-i\omega}\right)d\omega\right]}{\operatorname{tr}\left[\int_{-\pi}^{\pi}\Gamma(\omega)\, S_{\tilde{Y}_j}\left(e^{-i\omega}\right)d\omega\right]}\alpha. \tag{6}$$

The shock with the largest share of the FEV of variable j associated with the filter $\Gamma(\omega)$ is given by $\alpha^* = \arg\max_\alpha V_{\tilde{Y}_j}(\alpha)$. In principle, the choice of the filter, $\Gamma(\omega)$, can be ad hoc (e.g., HP filter) or governed by theory. For example, the standard long-run restriction would amount to maximizing the FEV as ω approaches zero. In practice, we can utilize a set of linear filters constructed such that the gain reflects, say, business-cycle or medium-run frequencies.

4 Technology Shocks

In this section, we analyze the effects of technology shocks in a bivariate VAR in labor productivity growth, $\Delta \log(Y/H)$, and hours per capita, $\log(H/N)$.[8] We consider technology shocks identified by the algorithm proposed in Section 3 for a variety of frequency windows. The sample covers the period 1948:Q2-2009:Q4. Previous studies have highlighted changes in the mean growth of productivity over the sample. We follow Fernald [2007] and demean

[7] The integrals in equation (6) can be computed by Gauss-Legendre quadrature [see Press et al., 2007, p. 183].

[8] Productivity growth is measured as the annualized log-difference of output per hour of all persons in the nonfarm business sector; hours per capita are included in logs and measured as hours of all persons in the nonfarm business sector scaled by the civilian noninstitutional population (16 years and over). The Haver mnemonics in the USECON database for productivity, hours, and population are LXNFA, LXNFH, and LN16N, respectively.

both productivity and hours, allowing for two breaks: 1973:Q2 and 1997:Q2 (see Table 1). Figure 1 portrays the two time series and their corresponding sample spectral densities after demeaning.

Using the notation introduced above, we have:

$$Y_t = \left[\Delta \log\left(\frac{Y}{H}\right), \log\left(\frac{H}{N}\right)\right]',$$
$$\bar{Y}_t = \left[\log\left(\frac{Y}{H}\right), \log\left(\frac{H}{N}\right)\right]' = F(L)^{-1} Y_t,$$
$$\tilde{Y}_t = \left[\log\left(\frac{Y}{N}\right), \log\left(\frac{Y}{H}\right), \log\left(\frac{H}{N}\right)\right]' = G(L)\, \bar{Y}_t.$$

The matrix polynomials, $F(L)$ and $G(L)$, that allow to recover productivity, $\log(Y/H)$, and output per capita, $\log(Y/N)$, are given by:

$$F(L) = \begin{bmatrix} 1-L & 0 \\ 0 & 1 \end{bmatrix},$$
$$G(L) = \begin{bmatrix} 1 & -1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

The reduced-form VAR is estimated with four lags, i.e., $p = 4$.

To estimate the reduced form of the VAR, we utilize Bayesian techniques. For the Gibbs sampler, we impose a Jeffreys [1961] prior on the reduced-form VAR parameters[9]:

$$p(A, \Sigma) \propto \det(\Sigma)^{-\frac{n+1}{2}}, \tag{7}$$

where $A = [A_1, ..., A_p]'$. The posterior distribution of the reduced-form VAR parameters belongs to the inverse Wishart-Normal family:

$$(\Sigma | Y_{t=1,...,T}) \sim IW\left(T\hat{\Sigma}, T-k\right), \tag{8}$$
$$(A | \Sigma, Y_{t=1,...,T}) \sim N\left(\hat{A}, \Sigma\left(X'X\right)^{-1}\right), \tag{9}$$

[9]We truncate the prior to rule out posterior draws that imply explosive roots in the VAR.

where $\hat{A}$ and $\hat{\Sigma}$ are the OLS estimates of A and Σ, T is the sample length, $k = (np + 1)$, and X is defined as

$$X = \left[x_1', ..., x_T'\right]',$$
$$x_t' = \left[1, Y_{t-1}', ..., Y_{t-p}'\right]'.$$

We identify five different "Max Share" technology shocks that maximize the FEV of productivity at different frequencies:

1. the business-cycle frequencies extracted by an HP filter of parameter $\lambda = 1,600$;
2. the business-cycle frequencies with a period between 8 and 32 quarters;
3. the frequencies corresponding to fluctuations with a "medium-run" period between 32 and 80 quarters;
4. the frequencies corresponding to fluctuations with a "medium-run" period between 80 and 200 quarters; and
5. the entire set of frequencies in $[-\pi, \pi]$.

The gain functions of the corresponding linear filters are reported in Table 2. The frequencies corresponding to a given interval of periods, $[l, u]$, are extracted with a BP filter [Christiano and Fitzgerald, 2003]. For comparison, we also consider the long-run identification strategy proposed by Galí [1999].

For each draw from the posterior distribution of the reduced-form VAR parameters given by equations (8) and (9), we identify a technology shock and construct impulse response functions (IRFs) and FEV shares. For each of the identification schemes described above, we obtain $5,000$ draws from the posterior distribution of IRFs to various technology shocks and the corresponding FEV shares at various horizons.

4.1 Results

We plot the median, 16^{th}, and 84^{th} percentiles of the posterior distributions of the impulse responses to a one-percent increase in productivity growth in Figures 2-3. As a basis for comparison, the impulse responses to the technology shock identified by the standard long-run restrictions are shown in the last column of Figure 3.

Two distinct technology shocks emerge from our identification schemes. The shock that maximizes the FEV of productivity at business-cycle frequencies—$\text{BP}_{8,32}$ and HP_{1600} produce almost indistinguishable IRFs—resemble the shock that drives RBC models. It induces positive comovement between productivity, output, and hours. The responses of output and hours are persistent and hump-shaped.

When maximizing the FEV of productivity at lower frequencies, the same shock emerges from different identification schemes—$\text{BP}_{32,80}$, $\text{BP}_{80,200}$, the entire set of frequencies, and long-run restrictions. On impact this shock generates an ambiguous output response with both positive and negative draws; eventually, output increases. This shock has a clear contractionary effect on hours: The median IRF is negative on impact and converges to zero from below. The persistent increase in productivity is similar to the one generated by the business-cycle shock described above.

Recall that the identified technology shock is a linear combination of the Cholesky shocks, where α^*—the appropriate column of a rotation matrix—gives the weights. Figure 4 shows the responses to the two Cholesky shocks. Figure 5 shows the posterior distributions of the rotation angle between the two Cholesky shocks, $\theta^* = \text{atan2}\left(\alpha_2^*, \alpha_1^*\right)$, where α_1^* and α_2^* are the two elements of α^*. First, note that, for the bivariate system, the first Cholesky shock (shown in the first column of Figure 4) appears consistent with the shock taken from the standard RBC model. This would suggest that, for the shock identified by the HP_{1600} or the $\text{BP}_{8,32}$ filter, the rotation angle between the two Cholesky shocks should be centered at zero. The first panel of Figure 5 reveals this to be true. For all the other frequency windows we consider, more weight is placed on (the negative of) the second Cholesky shock. The negative of this shock is similar to a contractionary technology shock.

Tables 3-5 show how much of the FEV of each variable the shocks explain at various horizons. The last row of Table 3 reports the Max Share of productivty associated with each shock, $V_{\log(Y/H)}(\alpha^{*})$. Both the business-cycle and low-frequency technology shocks explain most of the FEV of productivity at all horizons. The low-frequency shock's share approaches 100% as the horizon increases. In contrast, the business-cycle shock explains almost all of productivity at short horizons and more than 60% at long horizons.

The business-cycle frequency shock explains more than 50% of the FEV of output at all horizons. The medium-term/low-frequency shock explains very little of the FEV of output at short horizons—less than 15% up to two years. The FEV share of this shock increases above 70% at long horizons.

Both shocks we identify account for less than 25% of the FEV of hours at any horizon. The finding that technology shocks account for little of the variance of hours is commonplace in the literature. The FEV share of the business-cycle (low-frequency) shock increases (decreases) with the forecast horizon.

5 Conclusions

Since Galí [1999], technology shocks have been identified in VARs using long-run restrictions. In a recent paper, FOR—building on Faust [1998]—proposed a finite-horizon alternative to the long-run identification. Here, we extend their finite-horizon alternative to the frequency domain. We identify technology shocks by the rotation of the Cholesky factor that maximizes the FEV for a chosen frequency window. The frequency domain provides natural identifying restrictions as many macro models have implications for technology shocks at business-cycle frequencies.

Using a bivariate VAR with productivity and hours, we compare the identification over a number of frequency windows. The resulting impulse responses are broadly consistent for frequency windows outside the business cycle. The shock identified by these frequencies is contractionary in hours with essentially zero effect on output on impact. On the other hand, the shock identified by maximizing the FEV for business-cycle frequencies is more consistent with an RBC technology shock—hours rise weakly on impact and output rises unambiguously.

Another fundamental difference between the two types of shocks identified by the different frequency windows is at what horizon the shock has the greatest effect. For the contractionary shock, technology accounts for a relatively small share of the short-horizon FEV of productivity and output. At longer horizons, this shock explains more of the variation in both those variables. While the shock never explains a large portion of the FEV in hours, the amount explained declines as the forecast horizon grows. The shock identified by business-cycle frequencies—the shock most consistent with the RBC shock—behaves in the opposite manner, explaining more of productivity and output at short horizons and accounting for less variation as the horizon grows.

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Variable	**Sampe period**		
	1948:Q2-1973:Q1	1973:Q2-1997:Q1	1997:Q2-2009:Q4
$400 \times \Delta \log \left(\frac{Y}{H}\right)$	2.78	1.33	2.94
$\log \left(\frac{H}{N}\right)$	-7.54	-7.56	-7.53

Table 1: Average productivity growth and hours p.c.

Filter	$\boldsymbol{\Gamma}(\boldsymbol{\omega})$
HP_{λ}	$\frac{4\lambda[1-\cos(\omega)]^2}{1+4\lambda[1-\cos(\omega)]^2}$
$\text{BP}_{l,u}$	$1_{\left[\frac{2\pi}{u},\frac{2\pi}{l}\right]}$
All	$1_{[-\pi,\pi]}$

Table 2: Gains of various filters

Horizon	**Max Share**					**Long run**
	HP_{1600}	$\text{BP}_{8,32}$	$\text{BP}_{32,80}$	$\text{BP}_{80,200}$	All	
1	99.49 [97.60,99.95]	98.04 [90.85,99.03]	63.91 [48.92,76.97]	62.20 [37.13,83.30]	63.25 [27.45,90.84]	60.94 [19.75,92.53]
4	96.78 [94.65,98.12]	96.15 [91.02,97.87]	71.19 [58.71,81.11]	70.00 [46.76,86.79]	70.19 [36.80,92.12]	68.10 [27.98,92.88]
8	82.09 [72.25,89.74]	83.91 [70.67,91.09]	83.22 [76.35,88.70]	82.13 [68.25,90.08]	80.28 [58.71,89.71]	79.01 [51.69,89.51]
20	71.40 [50.10,88.06]	73.60 [46.42,91.46]	90.56 [86.37,93.47]	91.03 [85.36,94.82]	89.28 [78.56,93.81]	88.50 [73.92,93.52]
40	67.97 [36.66,91.02]	69.39 [32.93,93.33]	92.89 [85.25,95.72]	94.83 [91.61,96.82]	94.20 [89.13,96.68]	93.82 [86.46,96.50]
80	65.73 [26.73,92.65]	66.32 [22.58,94.07]	94.07 [79.63,97.28]	96.64 [93.38,97.96]	96.94 [94.39,98.27]	96.85 [93.63,98.21]
200	63.56 [20.61,93.83]	63.38 [16.39,94.91]	94.28 [74.09,98.53]	97.99 [92.99,98.97]	98.66 [97.16,99.26]	98.74 [97.65,99.28]
$V_{\log(Y/H)}(\alpha^*)$	77.27 [70.24,83.82]	72.29 [64.35,80.57]	93.63 [83.89,97.93]	97.85 [90.88,99.73]	98.70 [97.76,99.18]	100 [–]

Table 3: FEV share of productivity due to technology shocks.

Horizon	**Max Share**					**Long run**
	HP_{1600}	$BP_{8,32}$	$BP_{32,80}$	$BP_{80,200}$	All	
1	59.94 [48.62,70.32]	57.08 [36.96,76.67]	6.95 [1.42,16.26]	7.27 [0.76,22.92]	9.93 [0.94,39.05]	12.00 [1.13,44.95]
4	51.44 [40.22,61.80]	49.53 [30.28,67.62]	3.94 [0.88,11.42]	4.98 [0.91,17.59]	8.18 [1.11,34.22]	10.51 [1.38,40.26]
8	59.47 [48.63,69.49]	57.63 [39.39,73.63]	8.49 [2.39,18.76]	8.68 [2.28,24,69]	11.70 [2.62,40.93]	13.55 [2.76,45.40]
20	68.47 [59.29,76.19]	67.06 [50.77,78.59]	19.76 [10.88,30.39]	19.92 [9.00,37.01]	22.62 [8.71,51.64]	23.29 [9.09,54.44]
40	71.08 [62.36,77.72]	69.25 [58.45,77.09]	35.37 [23.82,45.38]	36.38 [22.82,50.75]	39.35 [22.30,62.07]	39.22 [22.60,64.55]
80	70.70 [53.55,80.23]	68.51 [51.56,78.13]	52.57 [39.69,62.13]	55.94 [42.56,66.94]	58.99 [43.80,74.47]	58.89 [44.08,75.68]
200	67.37 [35.78,86.03]	66.15 [33.03,84.30]	71.31 [53.73,79.70]	76.51 [65.92,83.39]	79.39 [69.94,87.60]	79.57 [70.07,88.28]

Table 4: FEV share of output per capita due to technology shocks.

Horizon	**Max Share**					**Long run**
	HP_{1600}	$BP_{8,32}$	$BP_{32,80}$	$BP_{80,200}$	All	
1	2.34 [0.29,7.18]	2.81 [0.27,12.69]	20.67 [9.52,35.22]	21.74 [6.10,46.54]	22.59 [3.32,57.14]	24.43 [2.87,66.19]
4	13.14 [5.40,22.92]	11.99 [2.76,28.72]	7.72 [2.33,18.41]	9.14 [1.91,27.96]	11.97 [2.06,40.86]	14.22 [2.25,49.47]
8	20.58 [10.08,32.31]	19.25 [5.89,37.73]	4.73 [1.94,13.19]	6.26 [1.97,21.48]	9.75 [2.31,35.38]	12.00 [2.49,43.75]
20	22.70 [11.32,34.95]	21.28 [6.76,40.10]	4.22 [1.57,11.89]	5.83 [1.72,20.47]	9.27 [2.23,34.35]	11.52 [2.37,42.71]
40	22.99 [11.42,35.37]	21.54 [6.86,40.44]	4.12 [1.46,11.83]	5.75 [1.61,20.38]	9.23 [2.18,34.28]	11.46 [2.32,42.52]
80	23.09 [11.42,35.45]	21.59 [6.88,40.49]	4.11 [1.43,11.84]	5.71 [1.59,20.36]	9.25 [2.17,34.27]	11.46 [2.31,42.54]
200	23.10 [11.42,35.50]	21.61 [6.88,40.40]	4.11 [1.42,11.86]	5.71 [1.59,20.36]	9.24 [2.17,34.23]	11.46 [2.31,42.54]

Table 5: FEV share of hours per capita due to technology shocks.

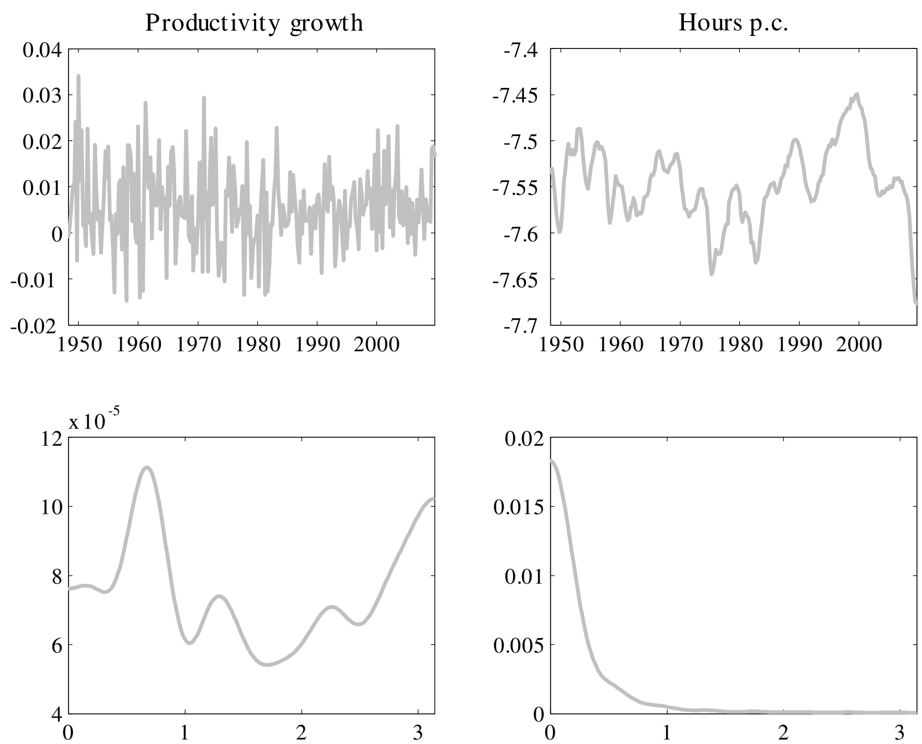

Figure 1: Data: time series (first row) and sample spectral densities (second row).

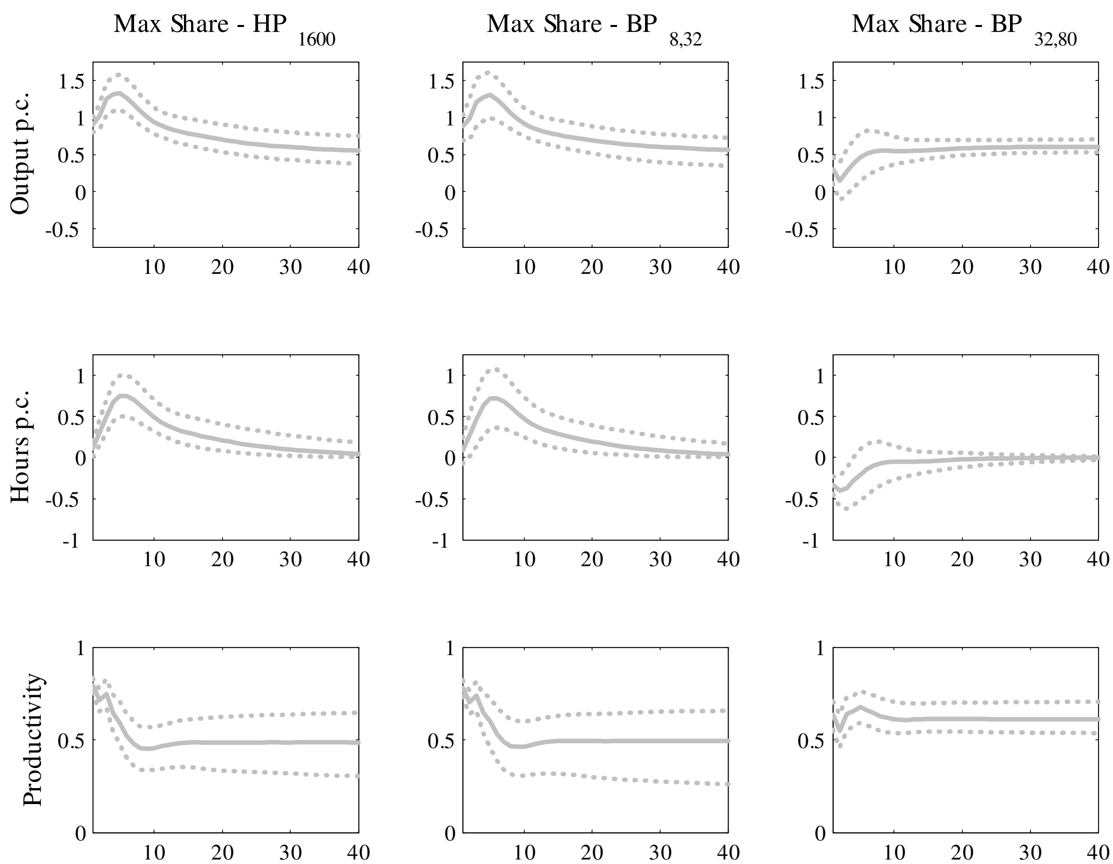

Figure 2: IRFs of hours, output, and productivity to various technology shocks (HP_{1600}, $BP_{8,32}$, $BP_{32,80}$).

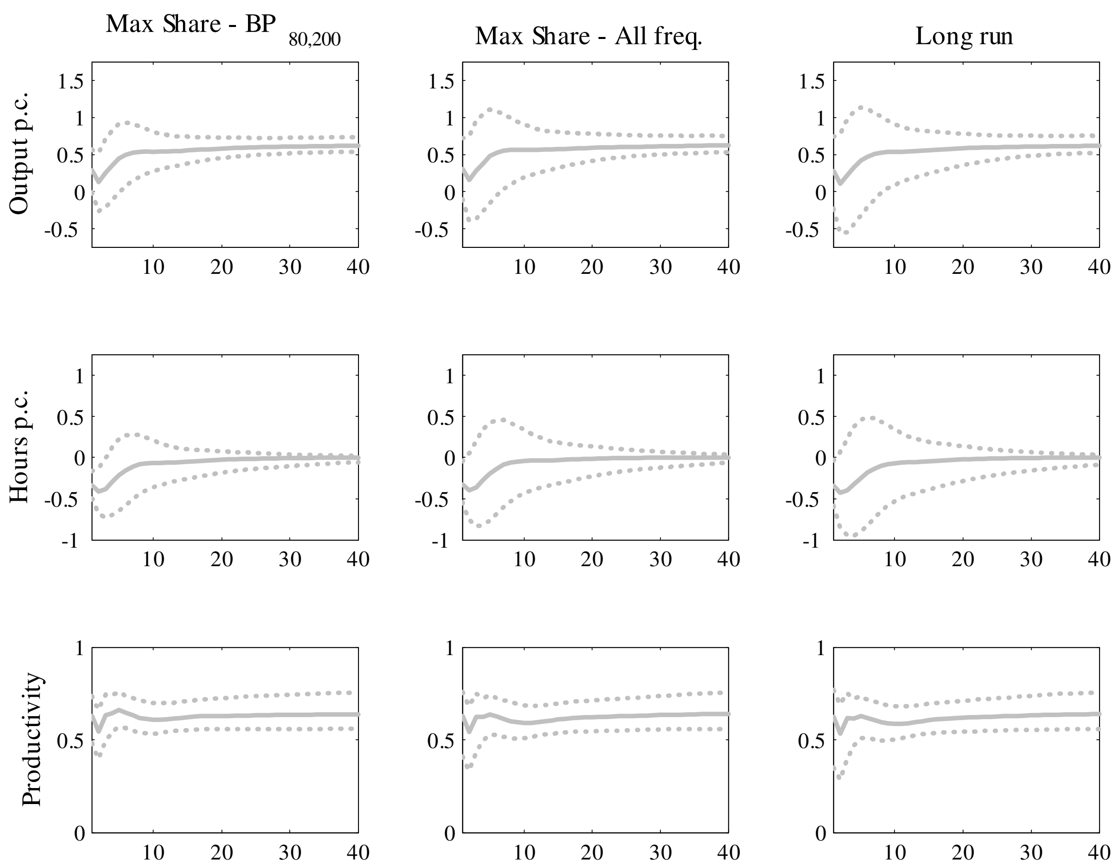

Figure 3: IRFs of hours, output, and productivity to various technology shocks ($BP_{80,200}$, all frequencies, long run).

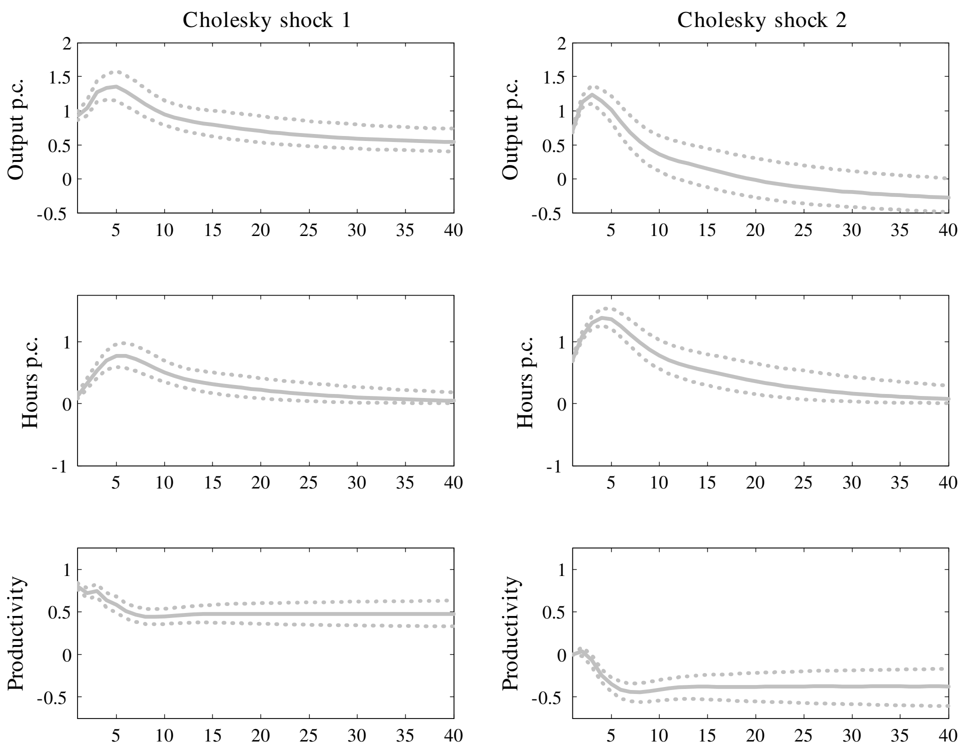

Figure 4: IRFs of hours, output, and productivity to Cholesky shocks.

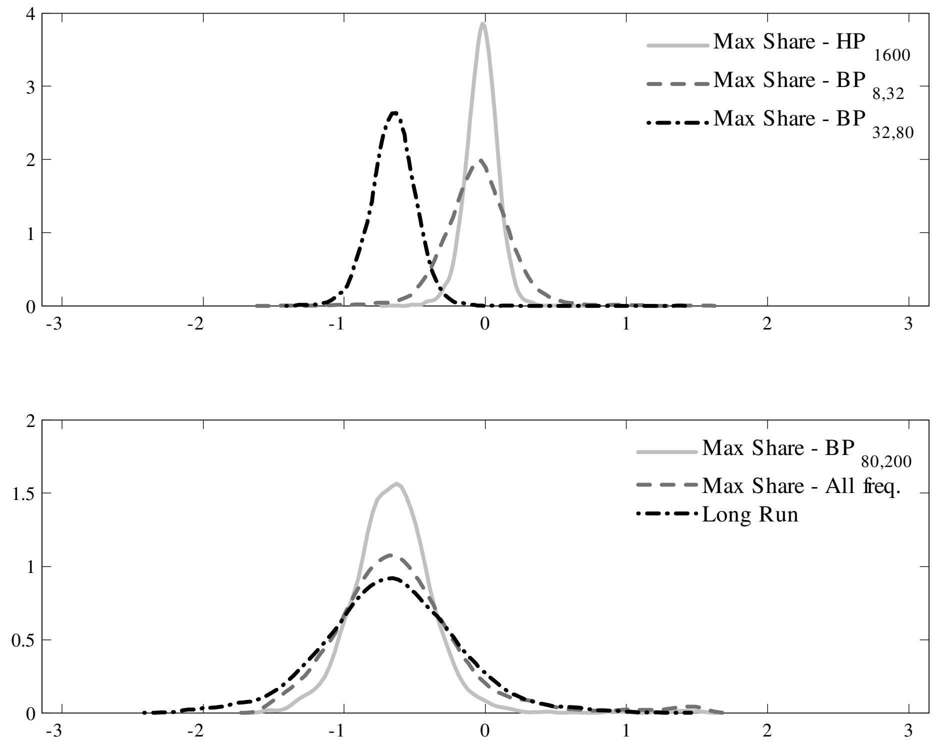

Figure 5: Posterior distributions of the rotation angle between Cholesky shocks, $\theta^* = \text{atan2}\,(\alpha_2^*, \alpha_1^*)$.